Economic/Emission Load Dispatch Using Artificial Bee Colony Algorithm

S. Hemamalini[1] and Sishaj P Simon[1]
[1] National Institute of Technology/ Department of Electrical and Electronics Engineering, Tiruchirappalli, India
Email: s_hemamalini@ rediffmail.com and sishajpsimon@ nitt.edu

Abstract—**This paper presents an application of the artificial bee colony (ABC) algorithm to multi-objective optimization problems in power system. A new multi-objective artificial bee colony (MOABC) algorithm to solve the economic/ emission dispatch (EED) problem is proposed in this paper. Non-dominated sorting is employed to obtain a Pareto optimal set. Moreover, fuzzy decision theory is employed to extract the best compromise solution. A numerical result for IEEE 30-bus test system is presented to demonstrate the capability of the proposed approach to generate well-distributed Pareto-optimal solutions of EED problem in one single run. In addition, the EED problem is also solved using the weighted sum method using ABC. Results obtained with the proposed approach are compared with other techniques available in the literature. Results obtained show that the proposed MOABC has a great potential in handling multi-objective optimization problem.**

Index Terms— **Artificial Bee Colony algorithm, economic emission dispatch, fuzzy decision, Pareto-optimal**

I. Introduction

The basic economic dispatch problem is to minimize the total generation cost among the committed units satisfying all unit and system equality and inequality constraints. However, the thermal power generation process produces harmful emission, which must be minimized for the environmental consideration. Many works are in literature as to solve the emission/economic dispatch problems. Several options are proposed to reduce unit emissions like installing cleaning equipments, changing to fuel with less pollutants or dispatching with emission considerations [1]. The first two methods involve more cost and thereby the third method is preferred. M.R.Gent and J.W.Lamont [2] have proposed a method for on-line steam unit dispatch that results in the minimum NO_x emissions. They had used a combination of a straight line and an exponential term for the total NO_x emission. J.Zahavi and L.Eisenberg [3] used a second order polynomial for representing NO_x emission. J.H.Talaq, E.El Hawary et al [4] gave a summary of economic environmental dispatching algorithms. A.A.El-Keib, H.Ma et al [5] describes a general formulation of the economic dispatch problem based on the requirements of Clean Air Act Amendments of 1990.

Kermanshahi et al. [6] used the sum of a quadratic and an exponential term. Nanda et al. [7] tried to find the best compromise between the conflicting targets of minimum cost and minimum emission by means of suitable multi-objective procedures. Granelli et al. [8] proposed an emission constrained dynamic dispatch procedure. It minimizes fuel cost during a pre-selected time horizon and thoroughly takes into account the environmental constraints. King et al. [9] reported an improved Hopfield Neural Network (NN) for the economic environmental dispatch problem. Wong and Yuryevich [10] developed an evolutionary programming based algorithm using emission as problem constraints. Das and Patvardhan [11] proposed a multi-objective stochastic search technique (MOSST) based on real coded Genetic Algorithm (GA) and Simulated Annealing (SA) using single criterion function optimization. Abido [12] presented a genetic algorithm based multi-objective technique, where multiple nondominated solutions can be obtained in a single run. In [13], Abido developed a multi-objective evolutionary algorithm that determined the Pareto optimal set simultaneously using the strength Pareto evolutionary algorithm. A comparison of nondominated sorting genetic algorithm [NSGA], niched Pareto genetic algorithm [NPGA], and strength Pareto evolutionary algorithm (SPEA) have been done in [14] for the environmental/economic electric power dispatch problem.

In this paper, a novel implementation of the multi-objective optimization problem accompanied by swarming intelligence approach is considered to obtain a best compromise solution between cost and emission minimization. The EED problem is solved using the ABC algorithm considering the objectives separately and as single objective using the weighted sum method. The feasibility of the proposed method is demonstrated on IEEE 30-bus test system. The results of MOABC are compared with the weighted sum method and with that of the results available in literatures.

II. Problem Formulation

Environmental/economic load dispatch involves the simultaneous optimization of fuel cost and emission objectives that are conflicting in nature satisfying the system and unit equality and inequality constraints. The general problem formulation is as follows.

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A. Multi objective EED Problem Formulation

The objective function of the non-linear constrained EED problem is formulated as in (1) to consider the cost of generation F_c and the emission control level E simultaneously.

$$\text{Minimize } F\,[F_c(P), E(P)] \tag{1}$$

$$\text{Subject to } \begin{cases} g\ (P) = 0, \\ h\ (P) \le 0. \end{cases}$$

where g is the system equality constraint, h is the inequality constraint and P is the set of variables to be optimized.

B. Objective Functions

Fuel Cost Function :

The fuel cost characteristics of each generator unit i, is represented by a quadratic equation as given in (2).

$$F_c = \sum_{i=1}^{N} (a_i + b_i P_i + c_i P_i^2)\ \$ \tag{2}$$

where a_i, b_i, c_i are the fuel cost coefficients of i[th] unit, N is the number of generating units, P_{imin} is the minimum generation limit of i[th] unit in MW, P_i is the power output of i[th] unit in MW and F_c is the total fuel cost in $.

Emission Function :

The emission from each unit depends on the power generated by that unit. This is modeled as a sum of a quadratic and an exponential function [2].

$$E = \sum_{i=1}^{N} (\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \zeta_i \exp(d_i P_i)) \quad \text{ton} \tag{3}$$

where α_i, β_i, γ_i, ζ_i and d_i are the emission coefficients of the generator i, and E is the total emission function in ton.

C. Constraints

1. Equality constraint:

   Real power balance constraint

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{4}$$

2. Inequality constraint :

   Real power generation limit

$$P_{imin} \le P_i \le P_{imax} \quad i = 1,2,..N \tag{5}$$

where P_D is the total load demand in MW, P_L is the total transmission loss in MW and P_{imax} is the maximum generation limit of i[th] unit in MW.

III. Multi-objective Optimization

The multi-objective optimization problem in its general form is as follows:

$$\text{Minimize } f_i(x) \qquad i=1,2,\ldots M; \tag{6}$$

$$\text{Subject to } \begin{cases} g_j(x) = 0, & j = 1,2,...J; \\ h_k(x) \le 0, & k = 1,2,...K; \end{cases}$$

$$x_{imin} \le x_i \le x_{imax}, \quad i = 1,2...n;$$

where a solution x is a vector of n decision variables: $x = [x_1, x_2, ...x_n]^T$,restricting each decision variable to take a value within a lower and an upper bound and f_i is the i[th] objective function. The terms $g_j(x)$ and $h_k(x)$ are called constraint functions. There are M objective functions and each objective function can be either minimized or maximized.

A. Pareto optimality

Having several objective functions, the aim is to find good compromises (or "trade-offs") rather than a single solution as in global optimization. The popular nondominated sorting procedure is used in this paper, to find multiple Pareto optimal solutions in a multi-objective optimization problem.

B. Fast nondominated sorting approach

To obtain Pareto optimal set of solutions a nondominated sorting algorithm proposed by Deb [15] is used. The approach is based on several layers of classifications of the individuals as suggested by Goldberg [16]. The population is ranked based on nondomination wherein all nondominated individuals are classified into one category. Then this group of classified individuals is ignored and another layer of nondominated individuals is considered. The process continues until all individuals in the population are classified. Since individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population. This allows searching for nondominated regions, and results in convergence of the population toward such regions.

C. Reducing Pareto set by calculating crowding distance

In some problems, the Pareto optimal set can be extremely large or even contain an infinite number of solutions. In this case, reducing the set of nondominated solutions without destroying the characteristics of the trade-off front is desirable from the decision maker's point of view. Crowded distance estimation approach [15] is employed to reduce the Pareto set to manageable size.

D. Best compromise solution

To extract the best compromise solution from a set of Pareto solutions in minimizing two conflicting objectives, fuzzy based mechanism is used. Due to the imprecise nature of the decision maker's judgement, the i[th] objective function of a solution in the Pareto optimal F_i is represented by a membership function μ_i [17] defined as in (7).

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$$\mu_i = \begin{cases} 1 & F_i \le F_i^{min} \\ \frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} < F_i < F_i^{max} \\ 0 & F_i \ge F_i^{max} \end{cases} \quad (7)$$

where F_i^{max} and F_i^{min} are the maximum and minimum values of the i[th] objective function respectively. For each nondominated solution k, the normalized membership function μ^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{M} \mu_i^k}{\sum_{j=1}^{m} \sum_{i=1}^{M} \mu_i^j} \quad (8)$$

where m is the number of nondominated solutions. The best compromise solution is the one having the maximum of μ^k.

E. Weighted sum method

In the EED problem, the cost function and emission function are weighted according to their relative importance and converted into a single objective function as in (9).

$$\text{Min} \quad f = wF_c + (1 - w)E \quad (9)$$

where F_c is the fuel cost function, E is the emission function and w is the weighting coefficient in the range 0 to1. When w=0, the function is an emission function and when w=1, the function is a fuel cost function. A trade-off can be obtained when w is varied from zero to one.

IV. Overview of Artificial Bee Colony Algorithm

Artificial Bee Colony (ABC) is one of the most recently defined algorithms by Dervis Karaboga [18], [19] in 2005. It has been developed by simulating the intelligent behavior of honeybees. In ABC system, artificial bees fly around in a multidimensional search space and the employed bees choose food sources depending on the experience of themselves. The onlooker bees choose food sources based on their nest mates experience and adjust their positions. Scout bees fly and choose the food sources randomly without using experience. Each food source chosen represents a possible solution to the problem under consideration. The nectar amount of the food source represents the quality or fitness of the solution. The number of employed bees or the onlooker bees is equal to the number of food sources or possible solutions in the population. A randomly distributed initial population is generated and then the population of solutions is subjected to repeated cycles of the search process of the employed bees, onlookers and scouts. An employed bee or onlooker probabilistically produces a modification on the position in her memory to find a new food source (solution) and evaluates the nectar amount (fitness) of the new food source. If the nectar amount of the new food source is higher than that of the previous one then the bee remembers the new position and forgets the old one. Once the employed bees complete their search process, they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. The onlooker bees evaluate the nectar information and choose a food source depending on the probability value associated with that food source using (10).

$$P_i = \frac{fit_i}{\sum_{j=1}^{N_e} fit_j} \quad (10)$$

where fit_i is the fitness value of the solution i which is proportional to the nectar amount of the food source in the position i and N_e (i.e. $N_{pop}/2$) is the number of food sources which is equal to the number of employed bees, n_e. Now the onlookers produce a modification in the position selected by it using (11) and evaluate the nectar amount of the new source.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (11)$$

where $k \in \{1, 2, \ldots, n_e\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. Although k is determined randomly, it has to be different from i. ϕ_{ij} is a random number between [-1, 1]. It controls the production of neighborhood food sources. If the nectar amount of the new source is higher than that of the previous one, the onlookers remember the new position; otherwise, it retains the old one. In other words, greedy selection method is employed as the selection operation between old and new food sources.

If a predetermined number of trials does not improve a solution representing a food source, then that food source is abandoned and the employed bee associated with that food source becomes a scout. The number of trials for releasing a food source is equal to the value of 'limit', which is an important control parameter of ABC algorithm. The limit value usually varies from $0.001 n_e D$ to $n_e D$. If the abandoned source is x_{ij}, $j \in (1,2,\ldots D)$ then the scout discovers a new food source x_{ij} using (12).

$$x_{ij} = x_{j\min} + rand(0,1) \times (x_{j\max} - x_{j\min}) \quad (12)$$

where $x_{j\min}$ and $x_{j\max}$ are the minimum and maximum limits of the parameter to be optimized. There are four control parameters used in ABC algorithm. They are the number of employed bees, number of unemployed or onlooker bees, the limit value and the colony size. Thus, ABC system combines local search carried out by employed and onlooker bees, and global search managed by onlookers and scouts, attempting to balance exploration and exploitation process [20].

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V. Implementation of MOABC for EED Problem

In this section, ABC algorithm [21] is implemented to determine the power output of each generating unit for a specified demand.

Algorithm

The step-by-step procedure for the proposed method is as follows.

Step 1: Specify generator cost coefficients, emission coefficients, generation power limits for each unit and B-loss coefficients. Initialize the four control parameters of the ABC algorithm and maximum cycle for the termination process.

Step 2: *Initialization of population with random solutions*

Initialize randomly an initial population $M = [X_1, X_2, ..., X_{N_{pop}}]^T$ of N_{pop} solutions or food source positions in the multi-dimensional solution space where N_{pop} represents the size of population. Each solution $X_i = [P_{i1} \quad P_{i2} \cdots P_{ij} \cdots P_{iD}]$, (i=1, 2,…, N_{pop} and j=1,2,…,D) is represented by a D-dimensional vector, where D is the number of parameters to be optimized. The elements of each solution vector denoted as x_{ij} is the real power output of generating units and they are distributed uniformly between their minimum and maximum generation limits using (12). The individuals generated should be refined to satisfy the constraint as in (4) and (5). Half of the colony size forms the employed bees.

Step 3: Evaluation of Fitness of the population

Evaluate the fitness value of each food source positions corresponding to the employed bees in the colony. A fitness function as in (13) is used.

$$\text{Fitness} = A[1 - \%\text{Cost}] + B[1 - \%\text{Emis}] + C[1 - \%\text{Error}] \quad (13)$$

where A, B and C (>0) are the weighting coefficients,

$$\text{Error} = \left| \sum_{i=1}^{N} P_i - P_L - P_D \right| \quad (14)$$

$$\%\text{Cost} = \frac{\text{Stringcost} - \text{Mincost}}{\text{Maxcost} - \text{Mincost}} \quad (15)$$

$$\%\text{Emis} = \frac{\text{Stringemis} - \text{Minemis}}{\text{Maxemis} - \text{Minemis}} \quad (16)$$

$$\%\text{Error} = \frac{\text{Stringerror} - \text{Minerror}}{\text{Maxerror} - \text{Minerror}} \quad (17)$$

where Stringcost and Stringemis are the individual string's cost and emission values of generation, Mincost and Minemis are the minimum objective function values of cost and emission within the population. Maxcost and Maxemis are the maximum objective function values of cost and emission within the population. Stringerror is the individual string's error in meeting the power balance constraint, Minerror is the minimum constraint error within the population and Maxerror is the maximum constraint error within the population. Mincost, Maxcost and Stringcost are calculated using the objective function (2), Minemis, Maxemis and Stringemis are calculated using the objective function (3) and Minerror, Maxerror and Stringerror are calculated using (14). Set the cycle count as one and repeat the following steps till the maximum cycle number (MCN) which is the termination criteria is reached.

Step 4: Modification of position and selection of site by employed bees

An employed bee produces a modification on the position (solution) in her memory for finding a new food source. The new food source is determined by altering the value of any one of the D parameters (old food source position), selected randomly using (11) and keeping other parameters unchanged. The modified position is then checked for constraints in (4) and (5). If the resulting value violates the constraint, they are set to the extreme limits. Then, the fitness value of the new food source position (new solution) is evaluated using (13). The fitness of the modified position is compared with the fitness of the old position computed in step 3. If the new fitness is better than the old fitness then the new position is retained otherwise the old one is retained in its memory. Here a greedy selection mechanism is employed as the selection operation between the old and new position. In case, if fitness value of the new position is less than the old one then a limit count is set.

Step5: Recruit onlooker bees for selected sites and evaluate fitness

After all employed bees complete the search process they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability P_i using (10) related to its fitness value [20].

Step 6: Modification of position by onlookers

As in the case of the employed bee discussed in step 4, the onlookers produces a modification on the position in its memory using (11) and checks the nectar amount of the candidate source. If the new food has equal or better nectar than the old source, it is replaced with the old one in the memory. Otherwise, the old one is retained in the memory. Again greedy selection mechanism is employed as the selection operation between the old and new position.

Step 7: Now, the position of employed bees and the unemployed bees obtained from step 4 and 6

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respectively are combined. The combined colony is sorted based on the nondomination sort. The new colony of employed bees of size $N_{pop}/2$ is formed and is updated in the Pareto set.

Step 8: Abandon sources exploited by the bees

If a solution representing a food source is not improved by a predetermined number of trials, then that food source is abandoned and the scout discovers a new food source to be replaced with X_i. The number of trials for releasing a solution is equal to the value of limit. This operation is performed using (12).

Step 9: Increment the cycle count. Stop the process if the termination criteria is satisfied. Termination criteria used in this work is the specified maximum number of cycles. Otherwise, go to step 4. N_{par} members of the colony belonging to the first front are saved as Pareto optimal solutions.

Step 10: To extract the best compromise solution from the Pareto optimal set, fuzzy based mechanism as discussed in section III (D) is used.

VI. Simulation Results and Discussions

In order to validate the proposed method, the EED is solved using the proposed method for IEEE 30-bus system. and has been implemented in MATLAB on a Pentium-IV, 1GB, 3.4 GHz PC. The maximum size of the Pareto-optimal set is chosen to hold 20 solutions. The ABC parameters are chosen by trial and error.

A. Test Case 1- IEEE 30 bus system

This test system comprises of 6 generators, 41 transmission lines and 30 buses. The cost coefficients, power generation limits and emission coefficients for the test case are adapted from [14]. The line data and bus data are as given in [22], [23]. In this case, the cost function is quadratic in nature and the emission function includes exponential term. Transmission losses are considered in this problem. The demand of the system is 283.4 MW. The population size and maximum number of generations have been selected as 100 and 300, respectively for the system under consideration. Limit value is set as 2 and the number of employed bees is equal to the number of unemployed bees. In order to explore the extreme points obtained by the proposed approach, fuel cost and emission functions are optimized individually. The result of best fuel cost and best emission when optimized individually are given in Table I and Table II. Table I and II show the results for optimized cost and emission, generation schedule, and losses for economic dispatch and emission dispatch when the two objectives are optimized individually. Generation schedules for each unit are given in p.u. on a base of 100 MVA. In Fig. 1 convergence characteristics of best fuel cost and best emission are shown.

Table I

Best fuel cost out of 20 runs

	NSGA [14]	NPGA [14]]	SPEA [14]	MOPSO [24]	MOABC
P1	0.1447	0.1425	0.1279	0.1207	0.0976
P2	0.3066	0.2693	0.3163	0.3131	0.3092
P3	0.5493	0.5908	0.5803	0.5907	0.6123
P4	0.9894	0.9944	0.9580	0.9769	0.9385
P5	0.5244	0.5315	0.5258	0.5155	0.5363
P6	0.3542	0.3392	0.3589	0.3504	0.3633
Cost ($/h)	607.98	608.06	607.86	607.79	605.9465
Emission (ton/h)	0.2191	0.2207	0.2176	0.2193	0.2180
Loss (MW)	-	-	-	-	2.3118

Table II

Best emission out of 20 runs

	NSGA [14]	NPGA [14]	SPEA [14]	MOPSO [24]	MOABC
P1	0.3929	0.4064	0.4145	0.4101	0.4039
P2	0.3937	0.4876	0.4450	0.4594	0.4484
P3	0.5818	0.5251	0.5799	0.5511	0.5464
P4	0.4316	0.4085	0.3847	0.3919	0.3994
P5	0.5445	0.5386	0.5348	0.5413	0.5428
P6	0.5192	0.4992	0.5051	0.5111	0.5253
Cost($/h)	638.98	644.23	644.77	644.74	644.1687
Emission (ton/h)	0.1947	0.1943	0.1943	0.1942	0.1942
Loss (MW)	-	-	-	-	3.2225

Now, the bi-objective optimization problem is solved using the proposed approach. The result for the best compromise solution of the combined economic emission dispatch problem is shown in Table III. Tables I, II and III reveal that the power output of each unit are well within the minimum and maximum limits of generation. It can be seen that the proposed approach is superior and preserves the diversity of the nondominated solutions over the trade-off front.

Table III

Best compromise solution-Case 1

	NSGA [14]	NPGA [14]	SPEA [14]	MOPSO [24]	MOABC
P1	0.2935	0.2976	0.2752	0.2367	0.2687
P2	0.3645	0.3956	0.3752	0.3616	0.3806
P3	0.5833	0.5673	0.5796	0.5887	0.5780
P4	0.6763	0.6928	0.677	0.7041	0.6726
P5	0.5383	0.5201	0.5283	0.5635	0.5267
P6	0.4076	0.3904	0.4282	0.4087	0.4344
Cost($/h)	617.8	617.79	617.57	615.00	617.1724
Emission (ton/h)	0.2002	0.2004	0.2001	0.2021	0.1999
Loss (MW)	-	-	-	-	2.7000

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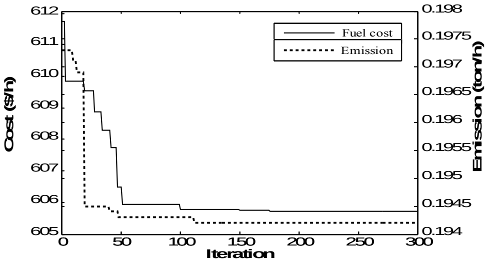

Fig.1.Convergence of best cost and best emission objective functions.

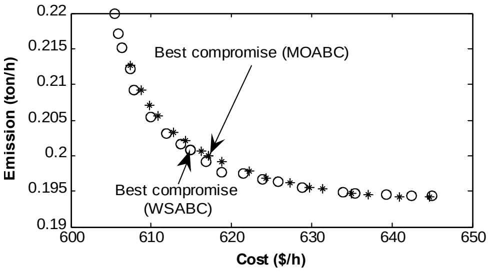

Fig. 2. Pareto-optimal front of the proposed MOABC approach.

For comparison, the same conflicting bi-objective problem is solved with ABC algorithm using weighted sum method in which the bi-objective function is converted into single objective function. In this method to obtain 20 nondominated solutions, the algorithm is applied 20 times, by varying w between 0 and 1 in steps of 0.05. The distribution of the nondominated solutions obtained in a single run using MOABC and in 20 runs for weighted sum ABC (WSABC) are shown in Fig. 2. In the single objective approach of solving the EED problem, the computation time taken to produce 20 solutions is 981.78 seconds. However, in the nondominated sorting MOABC method the time taken to produce 20 solutions is 157.02 seconds. This shows that the proposed method is faster than the classical weighted sum method. The results for single and bi-objective optimization using ABC algorithm is compared in Table IV. It can be seen that, the results for weighted sum method are closer to that of the multi-objective solutions. However, the computation time is very large in producing the same number of solutions as in MOABC.

TABLE IV

BEST SOLUTIONS FOR SINGLE AND MULTI-OBJECTIVE FUNCTIONS

No. of Objective functions	Best cost ($)	Best Emission (ton)	Best compromise	
			Cost ($)	Emission (ton)
Single	605.6725	0.1942	615.0303	0.2007
Multi	605.9465	0.1942	617.01	0.2000

VII. CONCLUSIONS

The proposed multi-objective ABC algorithm has been applied successfully to solve the bi-objective, non-convex EED problem. Nondominated sorting approach is used to find the Pareto set of solutions. The size of the Pareto set is maintained by computing the crowding distance, which preserves the diversity of the Pareto solutions. To obtain a best compromise solution from a set of Pareto solutions, fuzzy decision theory is used. The feasibility of the proposed method is demonstrated on IEEE 30 bus system. The EED problem is also formulated as a single objective function using weights and solved using the classical weighted sum method. Results obtained depicts that the proposed method is well suited to obtain a well-distributed Pareto optimal solutions in a single run. In addition, the comparison of the results with other methods reported in the literature shows the superiority of the proposed method and its potential for solving non-smooth EED problems in a power system.

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S. Hemamalini was born in India and received the B. E. degree in electrical and electronics engineering, and the M.Tech. Degree in power systems in 2005 from National Institute of Technology, Tiruchirapalli, India. She is currently pursuing Ph. D. degree in the Department of Electrical and Electronics Engineering, National Institute of Technology, Tiruchirapalli, India.
Her research interest includes Deregulation of Power System, Power System Operations and Control, Optimization techniques in power system.
Sishaj Pulikottil Simon was born in India and received his Bachelors of Engineering (Electrical and Electronics Engineering) and Masters of Engineering (Applied Electronics) at Bharathiar University, Coimbatore, India. He obtained his Ph.D., (Power System Engineering) at Indian Institute of Technology (IIT), Roorkee, India in the year 2006. Currently he is an Assistant professor in the Department of Electrical and Electronics Engineering at National Institute of Technology (NIT) (formerly Regional Engineering College), Tiruchirappalli, Tamil Nadu.

He has taught courses in Basic Electrical Engineering, Power Systems Planning and Reliability, Artificial Intelligence and Artificial Neural Networks. His field of interest is in the area of Deregulation of Power System, Power System Operations and Control, Application of Artificial Intelligence, and New Optimization Techniques to Power System.

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